Towards a Cognitive Framework for Assessing Students and Adapting Interventions in Extended Reality (XR)

Gregory McGowin
University Of Central Orlando, FL
gregory.mcgowin@ucf.edu

Joseph Cohn, J.T Folsom-Kovarik
Soar Tech
Orlando, FL
joseph.cohn@soartech.com, jeremiah@soar-tech.com

Tarah Daly, Georges Potworowski
Cognitive Performance Group
Portsmouth, Virginia
tarah@cognitiveperformance-group.com, georges@cognitive-performancegroup.com

Stephen M. Fiore
University Of Central Orlando, FL
sfiore@ucf.edu

Jennifer Phillips
Cognitive Performance Group
Portsmouth, Virginia
jenni@cognitiveperformancegroup.com

ABSTRACT

Consistent with the Chief of Naval Operations' priority to enable sailors to "operate in uncertain, complex, and rapidly changing environments" some of the most advanced educational resources may soon be delivered via immersive extended reality [XR] technology. Immersive XR can simulate the *affordances*—opportunities for decision and action provided by the environment—of complex situations presenting realistic multi-sensory cues within scenarios that support open-ended action. While XR technology provides capabilities that may improve learning, we argue that it requires thoughtful integration of instructional strategies and learning content *embedded* within the XR environment to maximize learning outcomes. Currently, no comprehensive, generalizable, theory-driven approach to delivering these interventions yet exists. Here we propose such a framework for delivering effective instruction and assessing real-time learner performance in a blended, adaptive XR instruction.

Our framework is based on the notion that cognition, the mental processes underlying learning, emerges through interactions between brain, body and environment. Using the *4E cognition model,* which views cognition as embodied, enactive, embedded, and extended, our framework characterizes the natural ways humans interact with their environments, laying the foundation for developing effective, intuitive learning experiences in XR We offer an adaptive training intervention framework that aligns affordances, 4E cognition, and instructional interventions to guide development and delivery of XR training.

Finally, any framework implementation requires metrics that capture student task competency in an XR environment, reflect intervention thresholds, diagnose the cause of performance shortfalls, or successes, so appropriate adaptative remediation or enhancements are selected. The Adaptive Contextualized Training in Interactive Virtual Environments (ACTIVE) framework offers a theory-driven approach integrating XR scalability, user-centered design, and real-time analytics for adaptive training. Contextualized through a Navy curriculum case study, we illustrate the framework's potential to enhance learning outcomes and training effectiveness.

ABOUT THE AUTHORS

Gregory McGowin is a PhD candidate in the Modeling and Simulation program at UCF and is a recipient of the Multidisciplinary Doctoral Fellowship. He holds a Bachelor of Arts in Psychology and a Master of Science in Modeling and Simulation from UCF. Mr. McGowin's multidisciplinary research interests focus on the intersection of cognition, technology, and learning. His current research centers on immersive VR and its utilization within the field of the learning sciences and is anchored in the philosophical and cognitive sciences theory of 4E cognition. His work aims to explore how technology can have transformative effects on learning and training, especially when integrated with interdisciplinary principles and frameworks.

Joseph Cohn is Director of SoarTech's Readiness and Medical Solutions team. A retired Navy Medical Service Corps Captain, Joseph developed and led a diverse range of teams to transition innovative science-driven biomedical and performance-enhancing capabilities across the Joint Force. At SoarTech, Joseph developed and implement strategic technology development focus for a team of 30 scientists and engineers to deliver Artificial Intelligence (AI) - enabled solutions to enhance human readiness, survivability and health. An expert in developing and executing technology strategies and roadmaps, Joseph is an Associate Fellow of the Aerospace Medical Association, a Fellow of the Society for Military Psychology and the American Psychological Association.

J.T. Folsom-Kovarik is a Senior Scientist at SoarTech and researches computer adaptive training systems that assess and adapt to learning needs. Dr. Folsom-Kovarik has contributed in research areas such as user model design, state and trait estimation during user interaction, robust performance modeling, computer understanding of speech and text, activity recognition, and algorithms that enable planning ahead for effective training. Much of this work has focused on adaptation to support individuals and teams in military training contexts. Key outcomes of his adaptive training research include improved user test scores, training time, self-efficacy, and transfer of training. Related research has also advanced cognitive ergonomics, decision presentation and explanation, and user control methods that help to increase the effectiveness, generality, trust, and acceptance of computer adaptive training systems as they interact with humans. Dr. Folsom-Kovarik earned a Ph.D. in computer science at UCF in 2012.

Tarah Daly is a Senior Scientist at the Cognitive Performance Group. With over 12 years of experience in research and development focused on human-centric solutions, Ms. Daly's expertise involves conducting usability and user-centered experience evaluations, conducting training effectiveness evaluations, and developing adaptive training solutions. Her research interests include individual differences in performance. She has disseminated research findings and theoretical implications in peer-reviewed, published works based on research in the Department of Defense, academia, and industry. Ms. Daly earned a M.S. in Modeling and Simulation and a B.S. in Psychology from the University of Central Florida.

Georges Potworowski is Director of Innovation and Marketing and a Senior Scientist at Cognitive Performance Group. He is an applied cognitive scientist with over 20 years of international experience researching, designing, and delivering interventions that support decision-making, learning, and performance. He uses an interdisciplinary, participative approach to co-design or improve processes and products from professional education courses and workshops to decision aids and user interfaces. He is currently guiding the design of the process and tools to support the iterative co-development of military technology and tactics for ONR. He has published peer-reviewed articles and chapters on professional training, meta-cognition, decision-making, teaching for wisdom, cognitive task analysis, mixed-methods research, and evidence-based practice. Dr. Potworowski earned a Ph.D. in Education and Psychology from the University of Michigan in 2010.

Stephen M. Fiore is Director, Cognitive Sciences Laboratory, and Pegasus Professor with the University of Central Florida's Cognitive Sciences Program in the Department of Philosophy and School of Modeling, Simulation, and Training. He maintains a multidisciplinary research interest that incorporates aspects of the cognitive, social, organizational, and computational sciences in the investigation of learning and performance in individuals and teams. His primary area of research is the interdisciplinary study of complex collaborative cognition and the understanding of how humans interact socially and with technology. He is Past President of the International Network for the Science of Team Science, and Past President for the Interdisciplinary Network for Group Research. He has contributed to working groups for the National Academies of Sciences in understanding and measuring "21st Century Skills" and was a committee member of their "Science of Team Science" consensus study. He is co-author of a book on Accelerating Expertise (2013) and is a co-editor of volumes on Shared Cognition (2012), Macrocognition in Teams (2008), Distributed Training (2007), and Team Cognition (2004).

Jenni Philips is the Chief Executive Officer and a Senior Scientist at the Cognitive Performance Group. Her research interests include skill acquisition, cognitive performance improvement, and the nature of expertise. Ms. Phillips applies cognitive task analysis and related techniques to model performance across the levels of proficiency, design learning solutions including decision-centered training scenarios and facilitation techniques and develop metrics for cognition and decision making. She is currently conducting Marine Corps research programs to measure adaptability and decision making in live and virtual force on force free play environments.

Towards a Cognitive Framework for Assessing Students and Adapting Interventions in Extended Reality (XR)

Gregory McGowin
University Of Central Flor-
Orlando, FL
gregory.mcgowin@ucf.edu

Joseph Cohn, J.T Folsom-Kovarik
Soar Tech
Orlando, FL
joseph.cohn@soartech.com, jere-miah@soartech.com

Tarah Daly, Georges Potworowski
Cognitive Performance Group
Portsmouth, Virginia
tarah@cognitiveperformancegroup.com, georges@cognitiveperformancegroup.com

Stephen M. Fiore
University Of Central Flor-
Orlando, FL
sfiore@ucf.edu

Jennifer Phillips
Cognitive Performance Group
Portsmouth, Virginia
jenni@cognitiveperformancegroup.com

INTRODUCTION

Some of the most advanced training tools are now, or soon will be, delivered via virtual reality (VR) and augmented reality (AR), collectively referred to as extended reality (XR), spanning the continuum from the real to the fully virtual world (Milgram & Kishino, 1994). The benefit of XR media for training is that it can simulate complex situations and scenarios, present realistic visual and audio cues, and play out the effects of open-ended learner actions across diverse education and training domains (Mikropoulos & Natsis, 2011). While XR offers significant potential, its effectiveness in training depends on careful design and implementation as there is no guarantee that XR alone will result in effective training.

As such, while XR offers significant promises for immersive scalable adaptive training, it also presents risks and failures, along with instructional and design limitations, that must be addressed to ensure its effectiveness. These can include:

- XR can engage and motivate students, but instructors or the training system must also detect and respond to distractions and off-task behavior.
- XR allows students to safely try what would normally be dangerous tasks or play out the consequences of mistakes, but the practical ability to simulate complex problems or allow varied student actions is limited by the effort and lack of reuse in implementing an instructional response for each one.
- XR allows many students to simultaneously explore models or practice skills, but scaling this capability is currently limited due to challenges instructors face in monitoring all students and providing personalized feedback to learners.
- XR can provide a wide range of scenarios and content, but without thoughtful design and focused monitoring by the instructor, there is the potential for negative training and transfer.
- XR alone might not fully leverage the benefits of traditional instruction, such as providing targeted examples and capitalizing on teachable moments. A blended solution can leverage the strengths of both adaptive XR and classroom instruction to create a more comprehensive and effective learning experience.

Implementing an adaptive system within XR poses a significant challenge. Despite extensive literature demonstrating the effectiveness of adaptive training systems in personalizing content and feedback (Kulik & Fletcher, 2016; Marraffino et al., 2021), no comprehensive, theory-driven approach fully leverages XR's potential for adaptive training. Interest in bridging this gap is growing, with recent research focusing on learning in immersive XR environments to enhance mediated learning (e.g., Makransky & Peterson, 2021; Mayer et al., 2023; Slater & Sanchez-Vives, 2016). However, a unified framework that integrates virtual environment learning, adaptive training, and XR's learning affordances is still lacking. Such a framework would enable the design of more effective, individually tailored instruction and support sophisticated, multi-component empirical assessments of instructional efficacy.
Delivering education and training capabilities at the scale necessary for deep and lasting impact requires a theory-driven paradigm shift that leverages the affordances of XR for adaptive training and addresses both the limitations

noted above and more pragmatic challenges: the high cost of designing XR systems; developing instructional capabilities that can accommodate complex concepts and large corpi of content; and adapting instructional remediation in a way that accounts for emergent student behaviors and variable paths to success

Limitations in Current Technology

Limitations and challenges in extant technology highlight the fragility, lack of scalability, and rapid obsolescence caused by atheoretical, one-off, hand-coded assessments and adaptive responses (Vergara et al., 2020; Sottilare & Van Lehn, 2023). To scale the benefits of adaptive XR, we need a technical approach to training, assessment, and adaptation that replaces one-off coding with flexible, reusable measures and interventions. This paper proposes a theory-driven, reusable (both in terms of the framework being applicable across a broad spectrum of XR learning environments as well as reusable technology itself), and technically advanced framework for assessing real-time student performance in adaptive XR instruction. The ACTIVE framework is designed to address these challenges and is characterized by three key aspects. First, we draw on theory on the affordances of XR grounded in the 4E cognition model (McGowin et al., 2021; McGowin et al., 2022; McGowin et al., 2023) and practical taxonomies of learning objectives and training interventions (e.g., Van Buskirk et al., 2009; Schatz et al., 2012) to frame the measurement of student performance and adaptation over XR learning progressions. Second, we recognize that XR environments are one modality for learning and assert that blended adaptive training, defined as the thoughtful integration of classroom instruction with technology-aided instruction (e.g., XR or online learning), is the most practical and cost-effective approach for educators and trainers to accelerate learning (e.g., Fegely & Cherner, 2023)[1]. Third, we employ a learner-centered design process to aid instructors. This framework leverages our general framework in the context of different knowledge and skill types to fully exploit XR affordances and help instructors understand student performance, thereby optimizing training and learning outcomes.

Adaptive Contextualized Training in Interactive Virtual Environments (ACTIVE) framework

To help remediate these limitations and address these gaps, we introduce the Adaptive Contextualized Training in Interactive Virtual Environments (ACTIVE) framework. This framework is a comprehensive approach designed to enhance adaptive training in XR settings. Grounded in theories of 4E Cognition and XR affordances framework (McGowin et al., 2023) as well as adaptive training (Martin et al., 2020), the ACTIVE framework aims to provide a general, actionable framework for monitorable, performance-based, as well as adaptive training in XR. The ACTIVE framework (see Figure 1) serves as a roadmap, linking XR learning theory and instructional design to the measurement of student competency on XR training tasks. It is a multidimensional approach designed to enhance adaptive training in XR environments through several key components. It begins with the *4E Cognition* model (element A of the figure), a theoretical construct that incorporates embodied, enactive, embedded, and extended cognition, viewing learning as a holistic process, and cognition involving more than simply information processing. This foundation is complemented by the identification of *XR Affordances* (B), which are eight unique features of mixed, immersive reality environments that facilitate cognitive development and inform instructional design. The framework then defines *Learning Objectives* (C), which are specific goals or outcomes enabled and accelerated by the XR affordances. Based on these learning objectives, appropriate *Training Interventions* (D) are selected and tailored to suit the needs of the learners, ensuring the

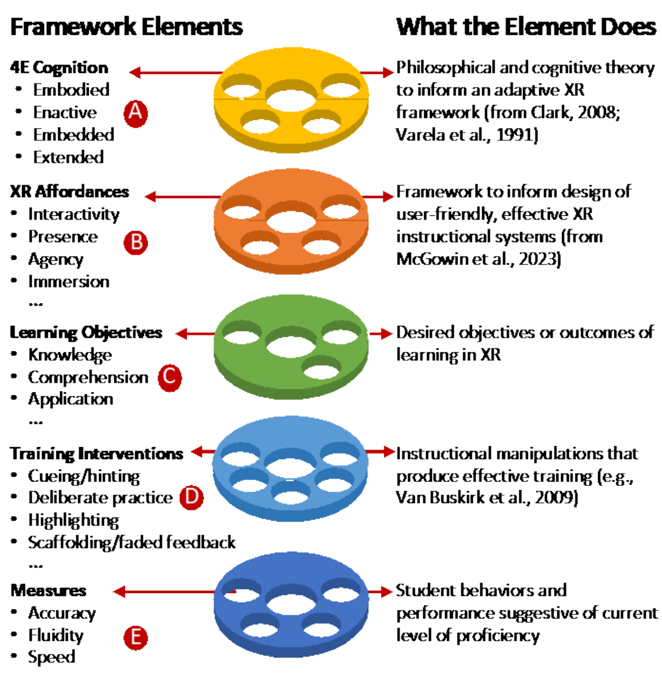

Figure 1. ACTIVE framework and its various elements

[1] Specifically integrating XR with classroom instruction (i.e., blended learning) is a future direction that the ACTIVE framework will investigate.

instructional strategies are effectively implemented within the XR system. Finally, the framework includes the *Assessment of Competency* (E), which involves real-time measurement of learner performance during XR training interventions. This continuous assessment allows for ongoing adjustments and improvements, ensuring the training remains effective and responsive to the learners' needs.
The ACTIVE framework addresses the need to evaluate the learning benefits of XR compared to more cost-effective counterparts, such as non-interactive media. It is particularly suited for scenarios where immersive experiences and spatial and bodily interactions may enhance learning and skill acquisition (Radianti et al., 2020; Hamiliton et al., 2021). This evaluation is important because it ensures that the specific tasks and learning objectives are met effectively and efficiently, catering to a variety of learners and modalities. Understanding the unique advantages of XR helps justify its use over traditional methods, ensuring that the investment in XR technology leads to improved educational outcomes and skill development.

Therefore, the purpose of the ACTIVE framework is to: 1) specify the unique affordances of XR that may call for its use in place of classroom and non-immersive technologies; 2) align learning objectives to training interventions suited for XR environments, akin to the Training Intervention Matrix constructed by Van Buskirk et al. (2009), Schatz and colleagues' Instructional Tactics (2012), or Stanney et al.'s (2023) ELEVATE-XR framework; and 3) define general measures of learning and skill acquisition that can be automatically collected from students' interactions with the training interventions. Thus, the ACTIVE framework is intended to guide instantiations of adaptive training in XR and serve as a set of testable theories for designing adaptive XR learning systems.

We believe that by providing a structured, theory-driven approach, the ACTIVE framework can help guide the design and implementation of adaptive XR learning systems, ensuring they are both effective and scalable.

In the pages that follow, we synthesize relevant theories of XR learning with practical considerations to assess whether and when learners are meeting learning objectives. We outline an adaptive framework that can change content to best support learner progress. To achieve this, we review current theories and practical applications, link these concepts together, and demonstrate the framework's effectiveness through virtual case studies. These case studies illustrate how an adaptive XR framework can dynamically adjust to optimize learning outcomes, ensuring learners meet their objectives efficiently and effectively.

BACKGROUND

XR and Learning Affordances

XR is increasingly being adopted in educational and training environments due to its unique capabilities to create immersive and interactive learning experiences. The potential of XR to enhance learning outcomes is largely attributed to its distinctive learning affordances (McGowin et al., 2023), which can leverage advanced technological and psychological mechanisms. These affordances include a core set that focuses on XR's ability to immerse learners in engaging environments (i.e., immersion, presence, interactivity, and agency) and a set of more specific concepts designed to leverage XR's unique capabilities to promote active learning and concrete experiences. These specific concepts, which have a rich history in the modeling and simulation literature, include transforming abstract to concrete, encouraging active participation over passive observation, turning what is infeasible due to cost or safety into the practically scalable, and exploring simulated manipulations of reality and beyond (i.e., instructional experiences that are not bound to strictly mimicking reality). See Table 1 for a more detailed explanation of the eight learning affordances of XR.

Table 1. Learning Affordances of XR.

Affordance	Description
Immersion	The degree to which an XR system realistically stimulates the user's senses, creating an inclusive, extensive, surrounding, and vivid illusion of reality. High levels of immersion are achieved through advanced technology that replicates human sensory experiences, allowing learners to feel fully engrossed in the virtual environment.
Presence	The psychological sensation of being in a different environment, where virtual objects are experienced as real through sensory or non-sensory means. This sense of "being there" enhances engagement and the perceived authenticity of the virtual experience.

Agency	The learner's ability to control and interact with the learning environment. It encompasses perceiving and acting on opportunities within the virtual space, with sensory-motor actions accurately reflected in the environment. This enhances the learner's sense of control and engagement.
Interactivity	The multidirectional exchange of information between agents (persons, systems, virtual agents) in a mediated environment. Characterized by the degree of modification, malleability, and feedback, high interactivity in XR may facilitate active learning by allowing learners to engage in dialoguing, controlling, manipulating, searching, and navigating within the virtual environment.
Concretization	The transformation of abstract concepts into concrete tangible experiences enhancing learners' understanding (ideally through embodied, enactive, and embedded interactions) where learners directly interact with and enact the content, facilitating deeper learning through multi-modal engagement. This helps learners grasp complex ideas by allowing them to interact with and visualize these concepts in a virtual setting.
Doing rather than only observing	Creating environments that closely resemble real-life situations, allowing learners to actively engage in practical tasks and simulations. This promotes better retention and understanding compared to passive observation.
Doing the infeasible or impossible	Enabling practice of tasks that are too dangerous, impractical, expensive, or improbable to perform in real life. Provides realistic training experiences by simulating rare, expensive, or extreme events in a safe and controlled environment.
Exploring manipulations of reality and beyond	Allowing learners to experiment with and manipulate scenarios beyond human capabilities, fostering new understandings and perspectives. XR can simulate effects of climate change or allow users to experience life from different social identities.

Note: Table adapted from McGowin et al., 2023.

Embodied, Enactive, Embedded, Extended (4E) Cognition

The theory of 4E cognition (cognition as embodied, enactive, embedded, and extended), posits that thinking and cognition result from dynamic interactions among the brain, body, and environment (Clark, 2008; Valera et al., 1991). Loosely defined, 4E cognition encompasses the interaction of a person's body or avatar (embodied cognition) within its environment (embedded cognition) and its engagement with external artifacts and agents (extended cognition) through reciprocal action and sensorimotor activities (enactive cognition) (Pouw et al., 2014). In other words, we rely on our bodies and senses to perceive and interpret the world around us, and as such, the specific characteristics of our bodies and sensory systems shape how we understand and interact with our environment, which in turn affects our cognition. 4E cognition can be seen as a synthesis of ideas from ecological psychology, cognitive science, and philosophy, also drawing on the concept of affordances as proposed by Gibson (1979) (Lobo et al., 2018). Affordances are actionable properties that emerge between agents and their environments, allowing direct interaction with the environment not merely through shapes and spatial relationships but through ecologically rich information about possible actions (Gibson, 1979; Norman, 1988). This theory suggests that higher-order information can be directly perceived and acted upon in ecologically valid contexts without the need for complex internal representations (c.f. Haselager et al., 2008). 4E cognition suggests that through direct perception and interaction with environmental affordances, cognition is distributed across the brain, body, and surroundings, thereby enhancing efficiency and performance (Fiore & Kapalo, 2017; Fiore & Wiltshire, 2016).

Linking XR, Learning Affordances, and 4E Cognition

Building on these foundational theories, recent research has suggested that immersive XR can provide learners with a range of authentic, contextually rich experiences that may promote positive skill transfer (Kaplan et al., 2021; Radianti et al., 2020). Meta-analytic findings show how technology-enabled active experiential learning strategies improve student performance in STEM disciplines (Shi et al., 2020). Other systematic literature reviews have shown similar findings, with XR generally, although not always, outperforming less immersive learning (Radianti et al., 2021; Hamilton et al., 2021). Linking XR, learning affordances, and 4E cognition provides a comprehensive way of understanding how these elements interact to enhance learning outcomes. To illustrate this, we now review some relevant examples.

One example comes from Jang et al. (2017), who compared active and passive learning environments using 3D-stereoscopic simulations in anatomy education. Active learners, who manipulated 3D anatomical structures, showed better outcomes than passive viewers. The ability to interact directly with content likely helped *concretize abstract* anatomical concepts, enhancing understanding. Additionally, the ability to *explore manipulations of reality and beyond*—such as viewing and interacting with anatomical structures in ways not possible in the real world—may have contributed to the improved learning outcomes observed in the active group.

Another example is from Seo et al. (2021), who conducted a usability study on VR anatomy education, focusing on the musculoskeletal system. The VR system allowed users to manipulate skeletal models (i.e., rotate, zoom), configure, and attach them together and to receive real-time visual feedback through a virtual mirror, helping them understand muscle movements and spatial relationships dynamically. This high level of *interactivity* likely contributed to users translating 3D models into an understanding of their spatial relationships. The real-time feedback from the mirror allowed users to see which muscles were contracting, with the system highlighting activated muscles for instant visual feedback, enabling an embodied understanding of muscle movements.

Extended cognition involves incorporating external elements to support or distribute cognitive effort (Fiore & Wiltshire, 2016). Examples include using phone reminders and calendars to supplement recall or internet searches to provide new information on demand. This concept is particularly relevant in the context of XR, where technologies can serve as external aids to enhance or scaffold cognitive performance (Estany & Martínez, 2014; Fiore & Wiltshire, 2016). Albus et al. (2021) provide support for this idea by investigating the use of annotations in VR to enhance learning about seawater desalination plants. Participants who used integrated textual annotations (i.e., extended cognition) outperformed those without them in terms of recall. This finding suggests that extending cognitive processes through external aids, such as annotations, can enhance recall performance in XR. While both groups had the similar levels of *interactivity*, it is probable that the offloading of important information (i.e., annotations) helped concretize their knowledge, allowing learners to *transform abstract* desalination concepts into tangible, understandable experiences.

XR does not simply simulate reality; it offers several advantages over real-world learning: 1) it enables learning in environments that are dangerous, rare, or hard to recreate in real life; 2) it can scale interactivity cost-effectively; 3) it can provide on-demand scaffolding; and 4) it can adapt to support individual paths. By providing highly *immersive* and *interactive* environments, XR can leverage learning affordances by allowing users to engage deeply with the material. Through the lens of XR learning affordances, the ability to manipulate and transform virtual objects (*interaction, agency*) help *concretize* abstract concepts. Additionally, real-time feedback and multi-angle viewing options support extended cognition, allowing learners to explore and understand complex spatial relationships dynamically and in an embodied way. This approach helps learners construct their own understanding through direct interaction, trial and error, and immediate feedback, which, we argue, are critical components of effective learning.

These examples illustrate how immersive XR environments can leverage 4E cognition principles, combined with the technological affordances of XR, to enhance learning outcomes. By actively engaging learners' bodies and senses, XR technologies provide contextually rich experiences that may promote deeper understanding and better skill transfer.

While these theories we have outlined above provide foundations for understanding how learning occurs, they often lack practical mechanisms for implementation into technological solutions. This is where adaptive training theories become essential, offering strategies to tailor educational experiences to individual learners' needs and enhance their engagement and retention. Through adaptive approaches, the relevance and applicability of learned skills are enhanced, and learner engagement, retention, and skill transfer may be increased. Combined, these approaches make XR particularly effective for training in complex environments where traditional methods may fall short.

Adaptive Training

Standardized learning often fails to accommodate individual differences and the varying levels of scaffolding needed at different stages of a learning progression. While the learning sciences, which draw from psychology, neuroscience, cognitive science, and educational theory, provide a deep understanding of how people learn, they often lack sufficient implementation methodologies. Applying these theories in real-world educational settings requires technical approaches that can effectively translate them into practice. Therefore, a general approach to transforming these theories into practical technical solutions is needed.

Adaptive training (AT) offers an effective solution that translates theoretical insights into impactful educational practices, fostering learning environments that are both adaptive and effective. AT is a method of instruction that utilizes technology to tailor the learning environment and materials to meet the specific needs and performance levels of each learner (Arroyo, et al., 2014). This approach aims to optimize the learning experience by providing personalized feedback (Koedinger & Corbett, 2001), dialogue (Graesser et al., 2012), resources (Ferilli, et al., 2022), and pathways (Magalong & Palomar, 2019) based on real-time data and learner interactions. As such, the core idea for AT is to create a customized learning journey that maximizes efficiency and effectiveness for each individual (i.e., individualized learning). AT systems function by monitoring and analyzing factors such as learners' performance, behaviors, biometric data, and interactions within the training environment. This data is then used to dynamically adjust the instructional content, difficulty level, feedback, or pacing to match the specific needs of each learner. By doing so, the system ensures that the learning experience is tailored to individual progress and challenges, facilitating better retention and transfer of training to new challenges (Ma et al., 2014).

There are various approaches to implementing AT, each leveraging different technologies and methodologies to help XR outperform conventional learning. Rule-based systems use predefined rules to adjust training content based on learner performance. For example, consistently correct answers might lead to increased difficulty, relying on expert-defined rules to guide adaptation. Machine learning algorithms analyze learner data to identify patterns and predict needs, providing highly personalized content through data analytics, focusing on automation rather than expert control. Cognitive tutors simulate human tutors by offering hints, feedback, and guidance based on the learner's performance and progression, adapting in real-time to individual needs. Intelligent tutoring systems (ITS) use AI to model learner knowledge and adapt instruction, aiming to provide personalized pacing, support, and guidance similar to one-on-one tutoring.

Each of these general approaches can be supplemented by additional technologies that help measure performance to gain deeper insight into an individual student's cognitive state. Integrating physiological, neurological, and other types of sensors can significantly enhance the effectiveness of AT technologies by providing deeper insights into the learner's state and enabling more precise adaptations (Folsom-Kovarik, et al., 2013). These supplemental sensors are expected to be more readily accepted in XR settings, as learners are already wearing technology such as a headset. Physiological sensors, like heart rate monitors and electrodermal response sensors, provide data on stress levels and emotional arousal, helping AT adjust content and difficulty to maintain optimal engagement. Eye-tracking devices monitor attention patterns, enabling the system to tailor the focus and presentation of information to enhance learning. Neurological sensors, such as electroencephalography (EEG) sensors, measure brain wave activity, providing insights into cognitive states like attention, concentration, and cognitive load (Sweller, 1988). This informs the system about when, how, and how much to adapt the complexity and pacing of the material. Functional Near-Infrared Spectroscopy (fNIRS) measures brain activity through blood flow changes, enabling adjustments in task difficulty and breaks based on cognitive workload (Causse et al., 2017,). Other types of sensors, including motion sensors like accelerometers and gyroscopes, detect physical movement, facilitating more interactive learning experiences or recognizing the need for physical breaks (Ogata & Ogawa, 2023). Wearable technology, such as smartwatches, monitors health metrics like physical activity, sleep, and stress levels, allowing the adaptive system to tailor learning schedules and intensity based on overall well-being (Bauer, et al., 2019). Thus, using sensors to monitor physiological and neurological states, AT systems can keep learners optimally engaged and motivated by preventing boredom and overwhelm. The sensors help detect or infer aspects of the learner's cognitive and emotional state, enabling responsive adaptation that enhances comprehension and retention. The sensors can also provide early detection of fatigue, stress, or disengagement, which allows for timely interventions such as breaks or motivational prompts, promoting sustained learning. As such, integrating diverse sensor data provides a holistic understanding of each learner, enabling highly personalized and effective learning experiences.

In summary, AT translates theoretical insights into impactful educational practices by utilizing technology to tailor learning environments and materials to meet the specific needs and performance levels of each learner. This approach optimizes the learning experience through personalized feedback, resources, and pathways based on real-time data and learner interactions. Various technologies (e.g., machine learning algorithms, ITS), modify instruction to enhance understanding and retention and help individualize learning. Integrating physiological and neurological sensors further refines this process, providing deep insights into learners' cognitive and emotional states, ensuring personalized and effective learning experiences.

XR is an excellent technology for embedding AT as it blends physical and digital environments, allowing real-time interaction with virtual and real-world elements to enhance learner outcomes. XR technologies can collect data from various sensors and performance inputs, enabling dynamic adjustments of content complexity and presentation based on real-time data from learner interactions, cognitive load, and emotional states. This ensures personalized, responsive training, catering to individual needs while providing immersive and interactive experiences. Furthermore, XR offers powerful learning affordances for adaptive training by embedding learners in realistic simulated scenarios, applying 4E cognition principles through coupling concepts with physical actions and multi-sensory input. It provides low-risk virtual spaces for practice and captures rich data on learner actions, behaviors, and physiological responses, making XR an effective platform for adaptive training.

BRIDGING ADAPTIVE TRAINING FRAMEWORK IN XR AND LEARNING AFFORDANCES

Adaptive training provides a *piece* of the solution to transform theory into practice, yet it still requires an instructional technology shell into which it can be inserted. AT frameworks typically involve dynamically adjusting the complexity, content, and presentation of instructional materials based on real-time data about the learner's performance, cognitive load, emotional state, and other relevant factors.

The ACTIVE framework provides a way to bridge AT frameworks with XR affordances. This framework suggests that adaptive instruction should be integrated within XR platforms to dynamically generate personalized training scenarios, adapt difficulty levels, provide tailored instructional support, and respond to learner states in real-time based on the multi-modal data captured. By leveraging the multi-modal data captured within XR environments, such as learner performance, physiological responses, and emotional states, these adaptive systems can adjust the difficulty levels and instructional support in real-time, ensuring an optimal learning experience. Overall, the integration of adaptive training within XR should not only make learning more engaging and effective but should also ensure that it is tailored to the unique needs and progress of each learner. This combination leverages the strengths of adaptive training theories and XR's technological and learning affordances, helping to create a comprehensive framework that bridges the gap between theoretical insights and practical application, ultimately maximizing learning outcomes.

IMPLEMENTATION OF ADAPTIVE TRAINING IN XR: CASE STUDIES

Our overarching goal is to produce a generalized framework that can be applied across multiple interdisciplinary domains. To demonstrate the practical application of the ACTIVE framework, we have selected two sample domains (engineering, medical) and provide two instances of adaptive instruction within each domain. Using the technology and theory discussed above, we show how the ACTIVE framework could be implemented to enhance learning outcomes in engineering education as well as improving training in complex medical procedures in the combat medical domain, showcasing its versatility and effectiveness across different fields.

These case studies illustrate how the ACTIVE framework assists stakeholders in making decisions in the design and development of effective adaptive XR training systems. As such, the framework helps stakeholders focus on clear solutions to their training needs. Currently, the framework is not prescriptive in nature and does not specify system requirements; rather, it offers a perspective for managing the design and development space of adaptive XR.

Engineering Domain

The U.S. Navy teaches Basic Electronics and Electricity (BEE) for surface engineering rates in Apprentice Technical Training (ATT). ATT is a ~13-week, full-time, classroom and lab course delivered between boot camp and Sailors' technical or job training in A school ('A' school is the initial rating-specific training where sailors learn skills for their chosen naval career field). ATT is a vital step to prepare Sailors for success in A school and on the job. The fundamental knowledge and skills in ATT are prerequisites that lay the groundwork for Sailors to understand and apply many of A school's learning objectives. However, ATT faces a number of challenges that can lead to negative learner outcomes. First, ATT encompasses a large volume of learning objectives, with material presented at a rapid pace. This can cause some individuals to quickly fall behind. Even a few days of falling behind can force a Sailor to restart ATT with a later cohort or leave the program altogether (i.e., attrition). The high course volume and swift pace can lead Sailors to adopt maladaptive learning strategies such as massed practice (i.e., cramming), which is associated with lower retention of skills and knowledge, increasing the speed of forgetting and skill decay (e.g., Soderstrom & Bjork, 2015). Second, ATT relies on older, simplistic materials. Classroom materials are strictly didactic, with self-study opportunities having little interactivity or adaptivity, and lab experiences lacking guidance or feedback. Lastly, ATT presents BEE in an artificial setting making it difficult for learners to perceive its relevance to future job tasks. This disconnect can hinder the transfer of training to job settings, even when the differences are minor, such as using a different version of a tool. Additionally, learners can experience negative training effects when practice circuits differ slightly from real devices, further hindering effective skill transfer.

The ATT setting provides an opportunity to apply the ACTIVE framework in designing a new, adaptive XR training experience. For example, using a breadboard—a standard, reusable teaching tool—in exploring basic electronics can transform abstract ideas into concrete concepts. Breadboards provide tangible, versatile platforms for prototyping and experimenting with circuits without soldering. This hands-on approach allows students to gain practical experience in component placement, circuit building, and troubleshooting, helping them transition theoretical knowledge to real-world applications and fostering a deeper understanding of electronics.

In an XR instantiation, a learner could engage with an interactive virtual breadboard. Unlike traditional computer-based training (CBT), this virtual breadboard allows students to physically walk around the virtual lab, view components from different angles, and interact with them in a realistic manner (*embodied, enactive; element A*). The *immersion* provided by XR (*element B*) makes learners feel as though they are inside a real electronics lab, further enhancing the sense of *presence* (*element B*) and making the experience more authentic (*embedded; element A*). Additionally, the XR environment enables dynamic *interactions* (*element B*) such as scaling, rotating, and zooming into objects. Learners can use hand gestures or voice commands to manipulate the virtual breadboard, experiencing *agency* (*element B*) in their learning process. Further, they can add virtual annotations to offload information as it is being learned and/or they are diagnosing (*extended; element A*). This contrasts with the point-and-click interface of CBT, offering a more natural and intuitive way to interact with the learning materials (i.e., agency in how they choose to interact). For instance, a learner might use hand gestures to pick up a virtual resistor, rotate it to read its color bands, and place it on the breadboard, all while receiving haptic feedback that mimics sensations of interacting with real objects. These *embodied* interactions help reinforce learning through the integration of physical movements and the *embedded* environment, which may improve skill acquisition and retention.

The XR system can adapt to the learner's level of competence by highlighting critical parts and providing "clickable" descriptions. Beginners might see color-coded guides showing where to place components, while advanced learners might receive complex circuit challenges without hints or additional cues (*adaption, feedback; element D*). This adaptive learning capability ensures that each learner receives the right level of challenge and support. The system could also track learner performance via relevant metrics (e.g., *accuracy, speed, fluidity of task completion*; *elements C and E*), providing real-time feedback while adjusting task difficulty accordingly (*element D*). This individualized approach helps address the challenging pace in ATT, allowing learners to progress at their own pace while still meeting course objectives. Furthering this example, visualizing the flow of electricity through cross-sectional overlays leverages XR's ability to represent complex spatial relationships. Learners can see animated electrons moving through the circuit, with overlays that show real-time data such as voltage and current at various points (*extended*). It is not only the richer *concretization* of abstract concepts but its combination with physical interactivity, that moves this far beyond what CBT can offer, making invisible phenomena like electrical flow tangible and understandable. These types of visualizations can be further enhanced by allowing learners to manipulate time (*agency, manipulation of reality and beyond; element B*), slowing down or speeding up the electrical processes to observe detailed interactions or long-term effects, providing insights that would be impossible in a physical trainer (*element D*).

Moreover, XR supports extended cognition by integrating tools like virtual multimeters and oscilloscopes. These tools can be used in real-time, allowing learners to probe circuits and see immediate feedback, both in terms of instrument information as well as guided feedback for learners, on their actions. For example, placing a multimeter probe on a circuit node could instantly display voltage reading combined with explanatory text, helping learners understand the practical implications of their theoretical knowledge. Additionally, the XR environment could also simulate *rare or dangerous scenarios*, such as improper use of a multimeter that would normally damage a circuit, as well as injected scenario events such as equipment failures or high-voltage situations, allowing Sailors to gain experience in critical situations without risk.

Medical Domain

In the U.S. Army, Combat Life Savers (CLS) and Combat Medics (designated 68W) are the first responders of the battlefield, and their training and skill maintenance is of preeminent importance to the military. While the instructors that train these groups are top-notch, their available tools to represent medical emergencies and practice responses on a person, while effective, are somewhat antiquated and could be improved with XR. Current tools include moulage, computer-based simulations, and field exercises. In the most hands-on case, simulated battlefield wounds are constructed from moulage (i.e., mock injuries) such as pre-made rubber wounds with fake blood that instructors apply during training. The simplicity of the presentation often requires the instructor to describe the wound to the trainee or remind the trainee during an exercise about the qualities of the wound that are not visually represented in the moulage, such as how the wound is responding to treatment. This effort by the instructors not only takes away time that could be spent providing instruction, but it also imposes an additional cognitive load on learners who must remember or imagine the specifics of these simulated wounds**.** While this approach doesn't limit the ability to practice *rare or complex scenarios*, it does make it more difficult for learners to contextualize the medical event and experience the sensory cues that should guide their decisions and actions. While simple, and generally effective, these physical simulations take considerable time and effort to create, set up, and manage, both before and during the training exercise. The preparation needed before each exercise, combined with the compressed training schedule of a CLS or 68W course, means that trainees receive limited hands-on practice in realistic settings. Additionally, while CBT simulations for CLS and Combat Medics are available, purely virtual training—whether on a 2D computer screen or in a full virtual reality environment—fails to provide embodied, enactive, embedded, and extended experiences as impactful as hands-on training that moulage wounds provide. This limitation of CBT underscores the need for a more immersive and interactive training solution that combines the benefits of both physical and virtual environments.

In terms of training that occurs in field exercises, it is even more simplistic: the state of the art is a "casualty card" that tells a randomly selected, non-trained "casualty" Soldier how to act given a wound described on the card. Without the use of moulage, the trainee sees no visible injuries on the actor playing the casualty, possibly increasing the cognitive load of the learner while reducing the realism and effectiveness of the training. This lack of visual and tactile cues possibly hampers the trainee's ability to develop diagnostic and treatment skills in authentic contexts. Thus, we argue that XR has the potential to revolutionize how CLS and 68W train for Tactical Combat Casualty Care (TC3) (i.e., prehospital procedures). XR can provide a unique mix of immersive digital simulation mixed with the real-world environment. For example, in a field exercise, a trainee could approach a casualty role-player or mannequin and see a simulated wound projected on the casualty. This combination of hands-on, tactile experience in the real world, alongside simulated, dynamic wounds and casualty responses, has the potential to drastically increase realism, effectiveness, and retention of medical training. Additionally, it may enhance learner engagement, improve skill transfer to real-world scenarios, and boost overall training outcomes. Additionally, XR can simulate environmental factors (e.g., low light conditions, noise, other stressors), providing a more comprehensive and realistic training experience that prepares CLS and 68W trainees for challenging conditions they may face in the field.

In an XR instantiation a dynamic wound model would be visually rendered, providing cues in the correct position on the casualty. This requires determining where the wound (and related visual cues such as blood flowing from the wound) should be placed based and then rendering visual and other wound effects such as the wound changing visually over time (e.g., based on treatments), audible and sensors cues associated with the wound (e.g., breathing sounds, pulse, respiration) (*immersion, presence, embedded, embodied; elements A and B*). The system could also project XR overlays on instruments the trainees use, such as overlaying an animation on top of the blood pressure gauge to show the representative blood pressure of the casualty rather than whatever the BP cuff would render from a live casualty or even a mannequin (*extended, abstract to concrete; elements A and B*); 2) a treatment recognition system could automatically recognize the procedures and interventions performed by the trainee, based on user sensors worn by the trainee and those on the moulage/casualty that can sense hand motions, the use of instruments, and pressure applied to different locations on the casualty or the wound (*measurement*, *embodied, enactive, agency; elements C and E*). Additionally, the system could use eye-tracking to infer the trainee's visual attention, decision making, and cognitive load, providing insights into their diagnostic approach. The treatment recognizer would then provide outputs of the sensors (e.g., user motions, verbalizations, instruments) and match those signatures against treatment models that describe what procedure or treatment is being performed. The output of this component is the identification of the recognized treatment, which is sent to the ITS; and 3) the ITS itself, which adapts the training scenario to the trainee according to the pedagogic goals database (defined for the scenario ahead of time by the instructor; *element C*). The training adaptation module would then respond to the treatments performed by the trainee (or lack thereof), in combination with pedagogic goals (i.e.,, learning outcomes; element C), to provide coaching or adapt the scenario in different ways – for instance to increase the level of difficulty for advanced students (i.e., introducing unexpected complications or secondary injuries), or to interject guidance for struggling students *(element D*).

CHALLENGES AND CONSIDERATIONS

Research in immersive XR learning needs to address several challenges, considerations, and future directions to maximize its effectiveness and applicability. In this paper, we outlined a multidimensional framework comprised of several elements aimed at enhancing XR-based training. However, due to the scope and constraints of this paper, not all elements were fully explored and developed. First, while we discussed the potential benefits of XR and highlighted some features that justify its use over classroom and non-immersive technologies, we did not fully specify and categorize these features. Future research should investigate and clearly define these features to better understand their impact on learning outcomes. Second, while we mentioned blended learning, which combines traditional instruction with XR, we did not thoroughly explore how to integrate this approach into the ACTIVE framework. Future research should focus on how blended learning approaches can be effectively applied to the ACTIVE framework, aiming to optimize the strengths of both traditional and XR methods and improve learning outcomes.

Third, while we discussed learning objectives in XR, we did not align specific learning objectives with training interventions suited for XR environments. Future work should develop a detailed Training Intervention Matrix, similar to those constructed by Van Buskirk et al. (2009) and Schatz et al. (2012), to ensure that XR training interventions are effectively matched to desired learning outcomes. Lastly, although the paper explored some potential measures of learning, we did not define general and specific measures of learning and skill acquisition that can be automatically collected from students' interactions with XR training interventions. Future studies should establish these measures to facilitate the assessment and improvement of XR training programs. By addressing these areas and limitations, future studies can further develop the ACTIVE framework, making it a more comprehensive and effective tool for planning and designing immersive XR learning experiences.

CONCLUSION

The aim of this paper was to synthesize relevant theories that are applicable to the design and development of adaptive XR training, including practical considerations for assessing when and how learners are meeting learning objectives, and to outline an adaptive system that can adjust content to best support learner progress. To achieve this, we reviewed current theories, practical applications, and provided a detailed description of the ACTIVE framework through virtual case studies. These case studies illustrate how an adaptive XR framework can dynamically adjust to optimize learning outcomes, ensuring that learners meet their objectives efficiently and effectively.

ACKNOWLEDGEMENTS

The authors wish to thank Ms. Natalie Steinhauser and her team at the Office of Naval Research (ONR) for their assistance with this paper and for their support of our research efforts.

REFERENCES

Albus, P., Vogt, A., & Seufert, T. (2021). Signaling in virtual reality influences learning outcome and cognitive load. *Computers & Education*, *166*, 104154. https://doi.org/10.1016/j.compedu.2021.104154

Arroyo, I., Woolf, B.P., Burelson, W., Muldner, K., Rai, D., & Tai, M. (2014). A multimedia adaptive tutoring system for mathematics that addresses cognition, metacognition and affect. *International Journal of Artificial Intelligence in Education,* 24, 387–426. https://doi.org/10.1007/s40593-014-0023-y

Clark, A. (2008). *Supersizing the Mind*. Oxford University Press.

Estany, A., & Martínez, S. (2014). "Scaffolding" and "affordance" as integrative concepts in the cognitive sciences. *Philosophical Psychology*, *27*(1), 98-111. https://doi.org/10.1080/09515089.2013.828569

Fegely, A., & Cherner, T. (2023). Bridging the XR Technology-to-Practice Gap: Methods and Strategies for Blending Extended Realities into Classroom Instruction, Volume II. *Association for the Advancement of Computing in Education.*

Fiore, S. M., & Kapalo, K. A. (2017). Innovation in team interaction: New methods for assessing collaboration between brains and bodies using a multi-level framework. In A. A. von Davier, M. Zhu, & P., Kyllonen (Eds.), *Innovative assessment of collaboration*, (pp. 51-64). Springer.

Ferilli, S., Redavid, D., & Di Pierro, D. (2022). An ontology-driven architecture for intelligent tutoring systems with an application to learning object recommendation. *International Journal of Computer Information Systems and Industrial Management Applications*, 14, 297-312.

Fiore, S. M., & Wiltshire, T. J. (2016). Technology as teammate: Examining the role of external cognition in support of team cognitive processes. *Frontiers in psychology*, *7*, 1531. https://doi.org/10.3389/fpsyg.2016.01531

Folsom-Kovarik, J.T., Wray, R. E., & Hamel L. (2013). Adaptive Assessment in an Instructor-Mediated System. In: H. C. Lane, K. Yacef, J. Mostow, and P. Pavlik (Eds.) *Artificial Intelligence in Education* in Lecture Notes in Computer Science (pp. 571–574). Springer. https://doi.org/10.1007/978-3-642-39112-5_61

Graesser, A. C., D'Mello, S., Hu, X., Cai, Z., Olney, A., & Morgan, B. (2012). AutoTutor. *In Applied natural language processing: Identification, investigation and resolution* (pp. 169-187). IGI Global.

Hamilton, D., McKechnie, J., Edgerton, E., & Wilson, C. (2021). Immersive virtual reality as a pedagogical tool in education: a systematic literature review of quantitative learning outcomes and experimental design. *Journal of Computers in Education*, 8(1), 1-32. https://doi.org/10.1007/s40692-020-00169-2

Haselager, P., van Dijk, J., & van Rooij, I. (2008). A lazy brain? Embodied embedded cognition and cognitive neuroscience. In *Handbook of cognitive science* (pp. 273-290). Elsevier. https://doi.org/10.1016/B978-0-08-046616-3.00014-1

Jang, S., Vitale, J. M., Jyung, R. W., & Black, J. B. (2017). Direct manipulation is better than passive viewing for learning anatomy in a three-dimensional virtual reality environment. *Computers & Education*, *106*, 150-165. https://doi.org/10.1016/j.compedu.2016.12.009

Kaplan, A.D., Cruit, J., Endsley, M., Beers, S. M., Sawyer, B. D., & Hancock, P. A. (2021). The effects of virtual reality, augmented reality, and mixed reality as training enhancement methods: A meta-analysis. *Human factors*, 63(4), 706-726. https://doi.org/10.1177/0018720820904229

Koedinger, K. R., & Corbett, A. (2001). Cognitive tutors. *Smart machines in education*, 145-167.

Kulik, J. A., & Fletcher, J. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research*, 86(1), 42-78. https://doi.org/10.3102/0034654315581420

Lobo, L., Heras-Escribano, M., & Travieso, D. (2018). The history and philosophy of ecological psychology. *Frontiers in Psychology*, *9*, 2228. https://doi.org/10.3389/fpsyg.2018.02228

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology*, 106(4), 901-918. http://dx.doi.org/10.1037/a0037123

Magalong, S. J. M., & Palomar, B. C. (2019). Effects of flipped classroom approach using Gooru learning management system on students' physics achievement. In *Proceedings of the 10th International Conference on E-Education, E-Business, E-Management and E-Learning* (pp. 75-78). https://doi.org/10.1145/3306500.3306540

Makransky, G., & Peterson, G. B. (2021). The Cognitive Affective Model of Immersive Learning (CAMIL): A theoretical research-based model of learning in immersive virtual reality. *Educational Psychology Review*, 33(3), 937-958. https://doi.org/10.1007/s10648-020-09586-2

Marraffino, M. D., Schroeder, B. L., Fraulini, N. W., Van Buskirk, W. L., & Johnson, C. I. (2021). Adapting training in real time: An empirical test of adaptive difficulty schedules. *Military Psychology*, 33(3), 136-151. https://doi.org/10.1080/08995605.2021.1897451

Martin, F., Chen, Y., Moore, R.L., & Westine, C, D. (2020). Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. Education Technology Research and Development 68, 1903–1929. https://doi.org/10.1007/s11423-020-09793-2

Mayer, R. E., Makransky, G., & Parong, J. (2022). The Promise and Pitfalls of Learning in Immersive Virtual Reality. *International Journal of Human-Computer Interaction*, *39*(11), 2229-2238. https://doi.org/10.1080/10447318.2022.2108563

McGowin, G., Fiore, S. M., & Oden, K. (2021). Learning affordances: Theoretical considerations for design of immersive virtual reality in training and education. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 65(1), 883-887. https://doi.org/10.1177/1071181321651293

McGowin, G., Fiore, S. M., & Oden, K. (2022). Me, myself, and the (virtual) world: A review of learning research in 4E cognition and immersive virtual reality. In *Virtual, Augmented and Mixed Reality: Applications in Education, Aviation and Industry* (pp. 59-73). Cham: Springer. https://doi.org/10.1007/978-3-031-06015-1_5

McGowin, G., Fiore, S. M., & Oden, K. (2023). Towards a Theory of Learning in Immersive Virtual Reality: Designing Learning affordances with Embodied, Enactive, Embedded, and Extended Cognition. In *Bridging the XR Technology-to-Practice Gap: Methods and Strategies for Blending Extended Realities into Classroom Instruction* (pp. 35-54). Association for the Advancement of Computing in Education.

Mikropoulos, T. A., & Natsis, A. (2011). Educational virtual environments: A ten-year review of empirical research (1999-2009). *Computers & Education*, 56(3), 769-780. https://doi.org/10.1016/j.compedu.2010.10.020

Milgram, P., & Kishino, F. (1994). A taxonomy of mixed reality visual displays. *IEICE TRANSACTIONS on Information and Systems*, 77(12), 1321-1329.

Pouw, W. T., Van Gog, T., & Paas, F. (2014). An Embedded and Embodied Cognition Review of Instructional Manipulatives. *Educational Psychology Review*, 26, 51-72. https://doi.org/10.1007/s10648-014-9255-5

Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & education*, *147*, 103778. https://doi.org/10.1016/j.compedu.2019.103778

Schatz, S., Bartlett, K., Burley, N., Dixon, D., Knarr, K., & Gannon, K. (2012, January). Making Good Instructors Great: USMC cognitive readiness and instructor professionalization initiatives. In *Proceedings of the I/ITSEC*.

Seo, J. H., Malone, E., Beams, B., & Pine, M. (2021). Toward Constructivist Approach Using Virtual Reality in Anatomy Education. In: JF. Uhl, J. Jorge, D.S., Lopes, P.F. Campos (Eds.) *Digital Anatomy: Applications of Virtual, Mixed and Augmented Reality* (pp. 343-366). Springer, Cham.

Soderstrom, N. C., & Bjork, R. A. (2015). Learning versus performance: An integrative review. *Perspectives on Psychological Science*, *10*(2), 176-199. https://doi.org/10.1177/1745691615569000

Shi, Y., Yang, H., MacLeod, J., Zhang, J., & Yang, H. H. (2020). College students' cognitive learning outcomes in technology-enabled active learning environments: A meta-analysis of the empirical literature. *Journal of Educational Computing Research*, *58*(4), 791-817. https://doi.org/10.1177/0735633119881477

Slater, M., & Sanchez-Vives, M. V. (2016). Enhancing our lives with immersive virtual reality. *Frontiers in Robotics and AI*, *3*, 1-47. https://doi.org/10.3389/frobt.2016.00074

Sottilare, R., & VanLehn, K. (2023). Intelligent tutoring Systems SWOT analysis. In: A. Sinatra, Graesser, A., X. Hu, G. Goodwin, & V. Rus (Eds.) *Design Recommendations for Intelligent Tutoring Systems: Volume 10.* Orlando, FL: U.S. Army Combat Capabilities Development Command – Soldier Center.

Stanney, K. M., Skinner, A., & Hughes, C. (2023). Exercisable learning-theory and evidence-based andragogy for training effectiveness using XR (ELEVATE-XR): Elevating the ROI of immersive technologies. *International Journal of Human–Computer Interaction*, *39*(11), 2177-2198. https://doi.org/10.1080/10447318.2023.2188529

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285, https://doi.org/10.1016/0364-0213(88)90023-7

Valera, F. J., Thompson, E., & Rosch, E. (1991). The Embodied Mind: Cognitive Science and Human Experience. MIT Press.

Van Buskirk, W., Cornejo, J., Astwood, R., Russell, S., Dorsey, D., & Dalton, J. (2009). A theoretical framework for developing systematic instructional guidance for virtual environment training. In *The PSI handbook of virtual environments for training and education* (pp. 97-113). Bloomsbury Publishing.

Vergara, D., Extremera, J., Rubio, M. P., & Dávila, L. P. (2020). The technological obsolescence of virtual reality learning environments. *Applied Sciences*, *10*(3):915. https://doi.org/10.3390/app10030915